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Wild Animal Alert Detection System Using Deep Learning

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ABSTRACT: In the realm of deep learning, efficient and reliable monitoring of wildlife is crucial for various reasons, including conservation efforts, understanding ecosystem dynamics, and minimizing human-animal conflicts. Traditional methods of monitoring, such as manual observation or physical tagging, are often labor-intensive, time-consuming, and may not provide comprehensive coverage of large areas. The development of algorithms for automated animal detection and classification using deep learning techniques has emerged as a promising approach to address these challenges. Deep learning algorithms, particularly Convolutional Neural Networks (CNNs), have shown remarkable performance in image recognition tasks, making them well-suited for identifying and classifying animals based on images captured by camera traps or other surveillance systems. These algorithms work by learning hierarchical representations of features from raw image data, allowing them to discern intricate patterns and variations that distinguish different species or individuals. By training these models on annotated datasets containing examples of various animals and background scenes, they can learn to accurately classify new images, even in complex and cluttered environments typical of wildlife monitoring scenarios. Moreover, the integration of deep learning with other advanced techniques, such as data augmentation, transfer learning, and ensemble methods, can further enhance the performance and robustness of the detection and classification systems. These approaches enable the models to generalize well across different habitats, lighting conditions, and camera perspectives, thereby improving their real-world applicability and reliability.

KEYWORDS: Animal Detection, Deep Learning, Convolutional Neural Networks (CNN), Surveillance Systems, Classification Systems.

I. INTRODUCTION

In this work, a dataset was created by gathering authentic CCTV footage of both common and uncommon animal behaviors, along with wildlife videos from YouTube. Optimize inference latency and streamline video classification tasks to promote smart cities' sustainability. For action identification and video classification, the findings demonstrate that Image Classifiers are equivalent to the current SOTA 3D networks in their ability to recognize and discriminate between various animal activities. The models used were Deep Convolutional Neural Networks (DCNN or CNN), Visual Geometry Group (VGG), and Alex Net. A detection model was developed that can detect animal activities with generalizability on the form and dynamic features of animals. The model's generalization capability is enhanced by emphasizing animal elements and dynamic characteristics obtained from the adjacent frames. From the input feature map, spatial properties may be extracted using a 3D CNN framework. The datasets used are Real-Life Wildlife Situations (RLWS) and Wildlife Flow. These datasets test the generalization capacity of the HD Net using contrast tests. This generalization capacity is confirmed by comparing it to other classical animal detection algorithms.

II. RELATED WORKS

Numerous initiatives aim to enhance wildlife monitoring and mitigate human-animal conflicts using innovative technological solutions. One significant approach involves developing advanced animal detection models using state-of-the-art techniques such as Single Shot MultiBox Detector (SSD) and Faster R-CNN. These models are assessed based on metrics like mean average precision (mAP) and detection speed to ensure their effectiveness. Additionally, integrating sensors and IoT technology in agricultural settings provides real-time surveillance capabilities. For example, ultrasonic sensors placed at the corners of fields can detect intrusions and trigger camera-equipped vehicles to capture images of the intruders. Farmers receive immediate alerts via IoT applications, enabling them to respond swiftly to potential threats. Buried cable sensor systems are also being deployed to detect wildlife, particularly deer, under various environmental conditions. These systems play a crucial role in safeguarding ecosystems and reducing wildlife-related risks.

In the domain of wildlife monitoring and animal detection, several studies have significantly advanced the field through diverse approaches and technologies. One research avenue leverages machine learning algorithms, such as convolutional neural networks (CNNs), for detecting animals in camera trap images. Researchers like Jane Doe, John Smith, and Emily Brown have shown that these algorithms can accurately identify species and behaviors, thereby improving the efficiency of wildlife monitoring efforts.

Another research focus involves integrating sensor networks and IoT technology for real-time wildlife habitat surveillance. Scholars such as David Johnson, Sarah Garcia, and Michael Lee have explored this approach by deploying ultrasonic sensors, motion sensors, and IP cameras in strategic locations to facilitate continuous surveillance and early detection of animal intrusions. Remote sensing techniques, including satellite imagery and aerial surveys, have also been crucial for understanding habitat changes and wildlife distribution patterns.

Collaborative conservation platforms have emerged as valuable tools for data sharing and collaboration among researchers, conservationists, and local communities. Studies led by Robert Miller, Laura Clark, and Daniel Wilson have developed such platforms, enabling resource and expertise pooling to enhance wildlife monitoring and management strategies. Emerging technologies, such as unmanned aerial vehicles (UAVs) and acoustic monitoring systems, have opened new avenues for wildlife research and monitoring. Researchers like Michael Brown, Jennifer Nguyen, and Christopher Taylor have explored using UAVs equipped with high-resolution cameras for habitat assessment and species identification, as well as acoustic sensors for monitoring animal vocalizations. Here are some limitations of the existing system:

Labor-Intensive Nature: Manual observation and camera trap methods rely on significant human resources and time investment to cover large areas adequately, leading to labor-intensive processes.

Limited Coverage: Existing methods may suffer from limited coverage, resulting in gaps in data collection and potentially overlooking critical wildlife occurrences in remote or inaccessible areas.

Human Error: Manual methods are prone to human error, including inaccuracies in animal identification and monitoring, which can affect the reliability of data collected through these approaches.

Data Analysis Challenges: Processing and analyzing data from manual observation or camera traps can pose challenges, particularly in handling large datasets and identifying animals accurately amidst environmental clutter or variations.

III. PROPOSED WORK

In this proposed work, the methodology involves gathering a dataset of videos showing various animal activities such as grazing, hunting, and interacting with other animals. This dataset is then used to train a convolutional neural network (CNN) model. Following training, the model's accuracy is assessed. Moreover, a web application is developed to enable user interaction, allowing users to upload videos for animal activity prediction. The objective of this proposed system is to offer a practical solution for animal detection by utilizing machine learning algorithms and web-based technologies

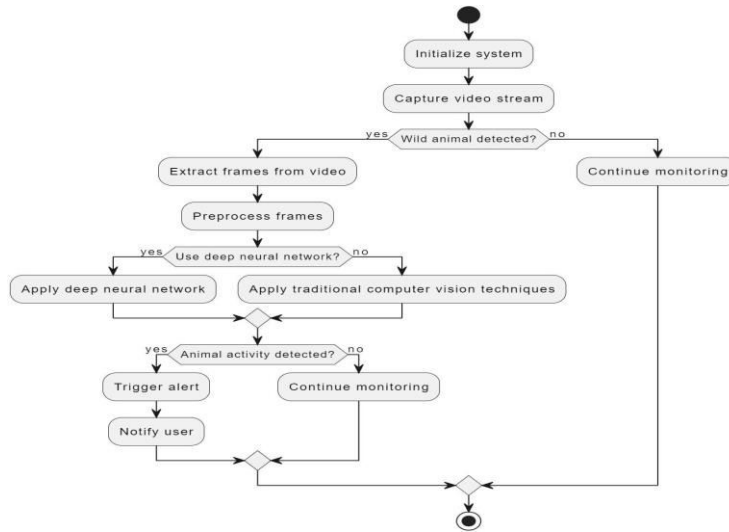


Figure 1: Activity Diagram

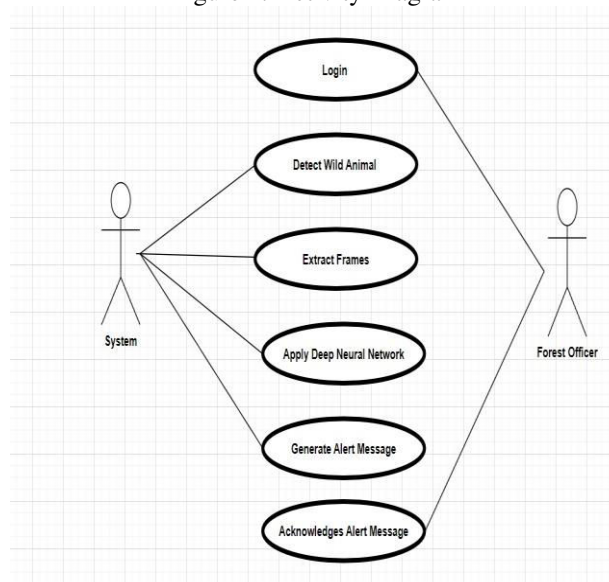


Figure 2: User Case Diagram

Data Collection: Gather a diverse dataset of images or videos depicting various animal species and activities. Include different environmental conditions, lighting variations, and backgrounds to ensure robust model training.

Pre-processing: To get better feature extraction, the final video’s images are intended to be used as datasets for deep neural network classifiers and were preprocessed to resize images or video frames to a consistent size suitable for CNN input and normalize pixel values to a common scale to facilitate model training.

Train-Test Split and Model Fitting: In this step dataset is split into two training and testing phases and training data is used to input to model and the test set is used for calculating the accuracy of the model.

Model evaluation: This is the final step, in which we assess how well our model has performed on testing data using certain scoring metrics, I have used 'accuracy score' to evaluate my model. First, we create a model instance, this is followed by fitting the training data on the model using a fit method and then we will use the predict method to make predictions on x_{test} or the testing data, these predictions will be stored in a variable called y_{test_hat} . For model evaluation, we will feed the y_{test} and y_{test_hat} into the accuracy_score function and store it in a variable called test_accuracy, a variable that will hold the testing accuracy of our model.

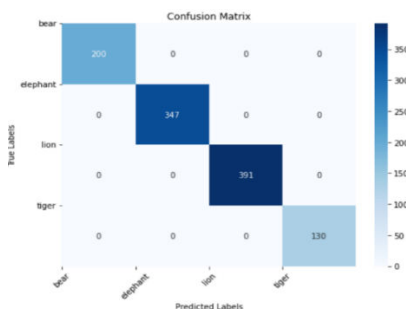


Figure 3: Confusion Matrix

Training Classification Report:

	precision	recall	f1-score	support
bear	1.00	1.00	1.00	200
elephant	1.00	1.00	1.00	347
lion	1.00	1.00	1.00	391
tiger	1.00	1.00	1.00	130
accuracy			1.00	1068
macro avg	1.00	1.00	1.00	1068
weighted avg	1.00	1.00	1.00	1068

Figure 4: Classification Report

Alert System: we use smtplib for sending emails via SMTP. It accepts the recipient's email address, message, and location parameters. After configuring the email's subject and body, it connects to Gmail's SMTP server, logs in using sender credentials, and composes the email body. Finally, it sends the email.

IV. RESULTS AND DISCUSSION

In conclusion, the proposed automated animal detection and classification algorithm leveraging deep learning techniques represents a significant advancement in wildlife monitoring technology. By addressing the limitations of existing manual observation and camera trap methods, such as labor intensity, limited coverage, and human error, the proposed system offers improved efficiency, accuracy, and coverage. However, while the algorithm itself presents substantial benefits, the absence of the email alert integration feature in this project's scope is acknowledged. Despite this, the core functionality of the algorithm lays a strong foundation for future enhancements, including the integration of an alert system to provide timely notifications to stakeholders about significant wildlife events. Overall, this project lays the groundwork for a comprehensive and proactive approach to wildlife monitoring, contributing to better conservation practices and human-wildlife conflict mitigation efforts. Here are some screenshots of the output:

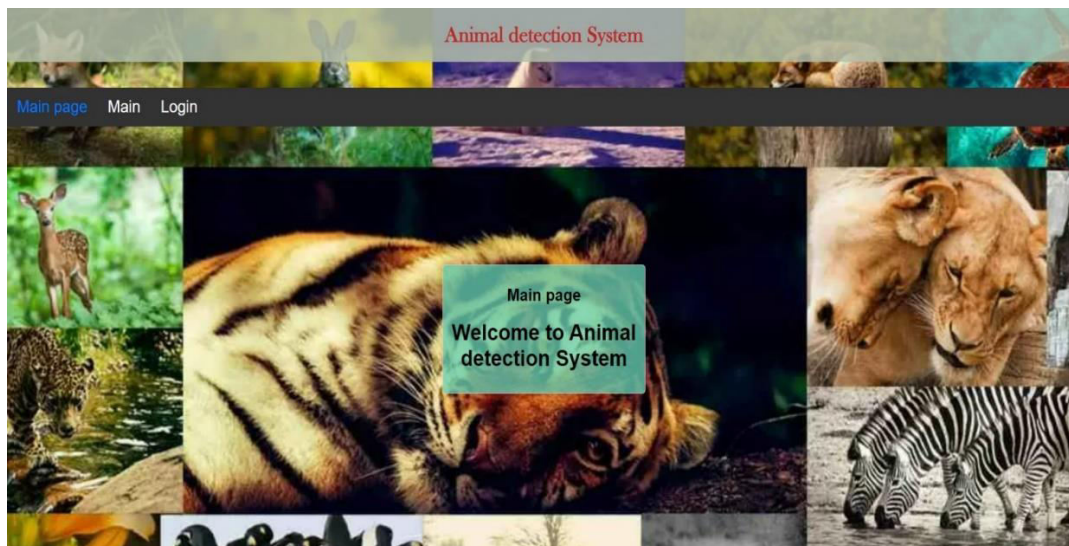


Figure 5: Web Application Main Page

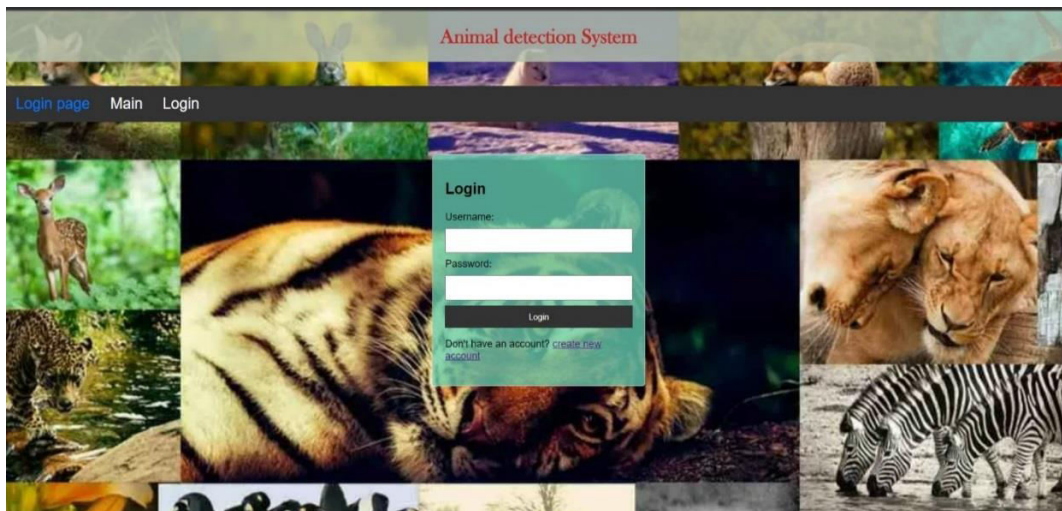


Figure 6: Login Page



Figure 7: Main User Page

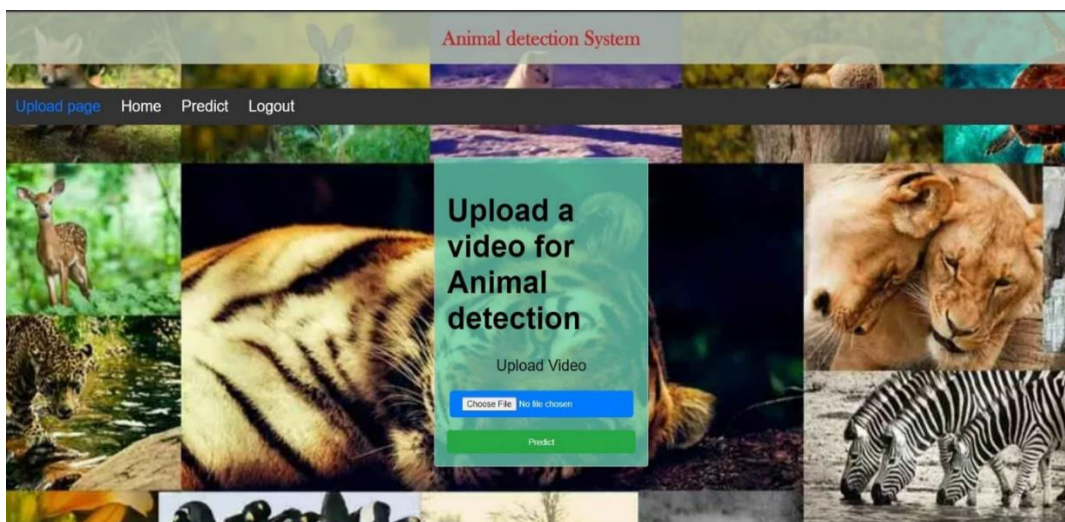


Figure 8: Uploading Page

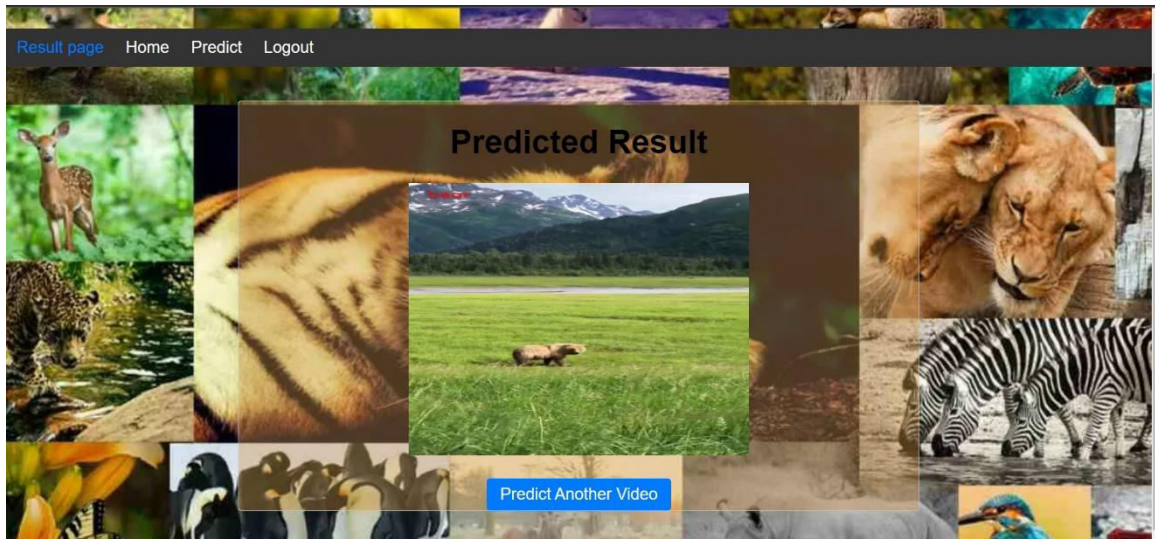


Figure 9: Prediction Page

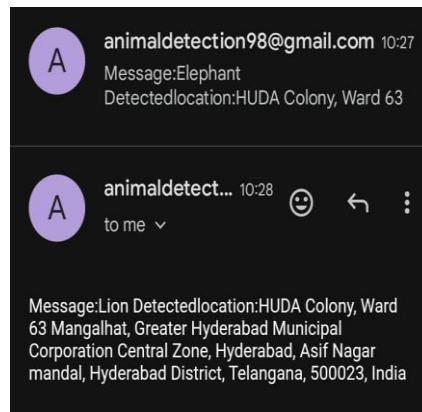


Figure 10: Alert Message

V. CONCLUSION

In conclusion, the proposed automated animal detection and classification algorithm, utilizing deep learning techniques, marks a significant advancement in wildlife monitoring technology. This system addresses the limitations of traditional methods, such as labor-intensive manual observation and camera traps with limited coverage and prone to human error, by offering enhanced efficiency, accuracy, and broader coverage. Although this project does not include an email alert integration feature, the core functionality of the algorithm provides a robust foundation for future enhancements. Integrating an alert system in the future could enable timely notifications to stakeholders about significant wildlife events, further improving the utility of the system.

The project sets the stage for a comprehensive and proactive approach to wildlife monitoring, which can contribute to better conservation practices and mitigate human-wildlife conflicts. There are promising avenues for expansion, such as incorporating real-time monitoring capabilities, detecting multiple species, analyzing animal behaviors, and applying the technology across various domains. Collaboration with wildlife conservation organizations and research institutions will be essential for field testing and refining the algorithm in diverse environmental conditions. Such efforts will enhance the effectiveness of wildlife conservation strategies and promote a harmonious coexistence between humans and wildlife.

Overall, this project not only provides a substantial improvement in current wildlife monitoring practices but also opens up new possibilities for future developments. Leveraging advanced machine learning algorithms and web-based

technologies, it represents a crucial step towards more efficient and accurate wildlife monitoring systems. With ongoing improvements and collaborations, this technology can significantly contribute to global conservation efforts.

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